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Utilizing unmanned aircraft system (UAS) technology to collect early stand counts and to assess early plant vigor for use in early-season stress tolerance characterization of hybrid corn products

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TABLE OF CONTENTS

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ABSTRACT

Early-season stress tolerance characterization of hybrid corn products relies heavily on early stand count and early vigor data from field trials in order to properly characterize products and to accurately assign stress emergence scores. The current manual collections of these data are labor-intensive, time-consuming, prone to human error, and in the case of vigor scoring, subjective. Unmanned aircraft systems (UAS) may provide a more accurate, rapid, objective, and efficient method for collecting stand count and vigor data resulting in higher quality products and overall cost-savings.

The purpose of this study was to determine if UAS could be used for stand count and vigor data collection for the early-season stress tolerance characterization of hybrid corn products. The early-season stress tolerance characterization field trial was flown on 12 different dates during the spring of 2017 representing plant growth stages from VE to V5. Stand count and plot cover values were calculated from the UAS obtained images for the 12 flight dates using a 2017 and an updated 2018 software algorithm. It was determined that the best time to collect UAS stand count data occurred at the V2 plant growth stage before leaf overlapping occurred. An UAS derived plot cover normalization method was also developed for assigning plot vigor scores allowing for more objective, reproducible, and unbiased assessments of plot vigor.

INTRODUCTION

An unmanned aircraft system (UAS), commonly known as a drone, is an aircraft without a human pilot onboard – instead, the UAS is controlled from an operator on the ground (FAA, 2018). With improving technologies, increasing capabilities, and greater availability, UAS has gained a lot of attention in recent years for use in expanded roles and applications beyond the military. Modern UAS has the ability to accommodate a wide range of civilian uses including recreational, industrial, commercial, and scientific research applications. Being inherently research and data driven, the seed industry may benefit greatly from the utilization of UAS technologies resulting in overall cost savings and higher quality products.

Research and development success within the seed industry relies heavily on generating and collecting high quality data on specific product traits of interest. Seeds embody the scientific knowledge needed to produce a new plant variety with desirable attributes such as higher yield potential, greater disease resistance, or improved quality (Fernandez-Cornejo, 2004). Much of the early-generation product research and development takes place in a lab and/or greenhouse setting, and is primarily focused on high-throughput molecular methods for screening large numbers of experimental products in order to identify the best for further advancement. The few products that are advanced require additional testing in a field environment to evaluate phenotypes, characterize traits, and to ensure product performance under a wide range of growing conditions.

Field data collection is often laborious, time-consuming, and frequently requires the coordination of multiple people working together in order to complete data collection tasks in a timely manner. As a result, field data collection can be expensive and may be prone to inaccuracies due to human error. Other data, such as trait ratings and/or scoring, are subjective in nature and may result in scoring inconsistences (Navarrete et al., 1997). UAS platforms may provide a more rapid, efficient, accurate, and objective way to collect field data for various research groups and applications.

Early-Season Stress Tolerance Characterization

Early-season stress tolerance characterization assesses a specific product's genetic ability to successfully emerge under a wide range of field conditions (Corn Seed Guide, 2018). Such characterization is becoming increasingly more important as farm operations are continuously consolidating and expanding, resulting in growers starting field activities earlier in the growing season. Seed companies are also looking to expand their markets by developing products for areas of more extreme latitudes with shorter and often more stressful growing seasons (Yadav, 2010).

Early-season stress tolerance is characterized by using a scoring system to assess stress emergence. A scoring system of 1 to 9 is used to score products with 1 being the least likely and 9 being the most likely to emerge under adverse growing conditions (Corn Seed Guide, 2018). A stress emergence score is assigned to a product using a combination of lab and field experiments. On the lab side, early-season stress tolerance is evaluated using a proprietary vigor test which has been proven to correlate well with field observations.

In the field, stress emergence experiments are conducted at multiple locations around the Midwest. Experiments are often planted in early spring and just ahead of a cold rain event if possible. Initial seed imbibition of near-freezing water creates severe stress and allows for observable product differentiation. Manual data collection in the form of early stand counts, early vigor scores, and early runt counts are conducted at the locations where adequate stress is encountered. The data from the field are then analyzed together with the data from the lab, and a stress emergence score is assigned to each hybrid corn product. With the help of UAS technology, it may be possible to remotely collect and analyze such field data of interest leading to a more efficient and higher quality early-season stress tolerance characterization of products.

UAS History

Much of the history of UAS can be found in military related applications including weaponization, reconnaissance, and surveillance. Some of the first recordable uses of unmanned aerial platforms for military weaponization include the use of unmanned hot-air balloons for aerial bombardment. Such platforms were used in the air raid of Venice by Austria in 1849 with similar devices used during the American Civil War (Watts et al., 2012).

Reconnaissance missions utilizing unmanned aerial platforms were implemented a short time later as improved cameras were developed. Corporal William Eddy of the US army used remotely-triggered cameras aboard kites in the 1898 Spanish-American war (Watts et al., 2012). World War I was responsible for encouraging the growth of both manned and unmanned aviation. Both the Army and the Navy began experimenting with the concept of “aerial torpedoes,” the precursor of today’s cruise missile, as a way to break the stalemate caused by nearly four years of trench warfare (Kearne and Carr, 2013). In 1918, the U.S. Army built the Kettering Bug, the first aerial torpedo using gyroscopic controls, but the war ended before it could be used (Vyas, 2018).

Surprisingly, most of the world’s aviation efforts in unmanned aircraft during the interwar period following World War I did not pursue weapon platforms like the aerial torpedo, but instead focused primarily on developing unmanned aircraft technology to be used as target drones for fighter pilot anti-aircraft gunnery training (Barnhart et al., 2012). In the 1930's the U.S. and British militaries began experimenting with radio-controlled aircrafts, which resulted in the development of the U.S. Curtiss N2C-2 Drone and the British DH-82B Queen Bee radio-controlled target (Vyas, 2018). World War II spurred further advancements in unmanned aircraft systems as critical technologies surrounding automatic stabilization, remote control, and autonomous navigation improved.

Much of the modern focus of UAS usage starting during the WWII era followed a consistent operation pattern described today as the three D's; Dangerous, Dirty, and/or Dull missions in which human pilot operations would be at a disadvantage or at high risk (Barnhart et al., 2012; Watts et al., 2012). Improvements in reconnaissance and guidance capabilities resulting from the Cold War as well as the Korean and Vietnam wars spurred interest among the scientific community in utilizing UAS for science missions in which pilotless aircraft provided similar advantages and risk mitigation (Watts et al., 2012). The U.S. National Aeronautics and Space Administration (NASA) played a significant role in the implementation of UAS for use in scientific research. NASA's unmanned aircraft for high-altitude atmospheric sampling during the "Mini-Sniffer" program of the 1970s-1980's and their Environmental Research Aircraft and Sensor Technology (ERAST) program in the 1990s marked the first major steps towards developing the protocols and capabilities for employment of UAS supporting scientific research (Watts et al., 2012).

UAS for military applications saw a resurgence following the 9/11 terrorist attacks in the "War on Terror." In addition to surveillance and reconnaissance type UAS operations, hunter-predator type drones such as the MQ-9 Reaper were largely implemented (Desjardins, 2016). As a result of this on-going conflict, several technological improvements surrounding sensors, imaging, and GPS navigation emerged. Miniaturization of critical UAS components also led to smaller-class and more affordable UAS platforms, paving the way for expanded roles and uses beyond military applications (Watts et al., 2012).

Current UAS Applications

Although the military market for UAS applications is still currently the largest, the civilian market is growing rapidly. According to a Business Insider article, the market for commercial and civilian drones will grow at a compound annual growth rate (CAGR) of 19% between 2015 and 2020, compared with 5% growth for the military market (Joshi, 2017). Some of the major driving industries and uses behind the rapid growth include: agriculture, construction, insurance, real estate, applied sciences, law enforcement, media, film, mining, utilities, private security, search and rescue, and wildlife conservation (Desjardins, 2016).

The number of published patents related to UAS applications have grown exponentially since the early 2000's leading to several technological breakthroughs and further fueling stimulation and growth of the UAS market (Desjardins, 2016). According to a Business Insider report, the total drone market today is valued at approximately $10 billion, and by 2025 will reach close to $13 billion (Business Insider, 2016). As a result of this rapid growth, the United States alone could see an economic impact of $82 billion while adding 100,000 jobs to the U.S. economy (Economic Report, 2017).

One of the more promising emerging fields for UAS applications is the agriculture industry. According to a Bank of America Merrill Lynch Global Research Report, nearly 80 percent of the future commercial UAS market will be dedicated to agriculture (French, 2015). Both crop and livestock operations are inherently dynamic and can benefit greatly from frequent observation and measurement. Modern UAS platforms allow for flexible, affordable, and efficient options for crop and livestock monitoring and management. They give producers a more complete view of their operation while enabling them to rapidly identify and respond to encountered issues as they arise.

Precision agriculture methodologies in crop production have expanded in recent years, and UAS have played an important role in the growth and effectiveness of such platforms. Some of the ways UAS have been utilized in precision crop production operations include determining emergence percentage and plant populations, and by identifying and monitoring nutrient deficiencies, diseases, insect damage, weed infestations, and moisture stress (Bedord, 2015). Having access to such data in near real-time enables producers to adjust and fine-tune input applications leading to a more efficient and environmentally sound operation.

Livestock producers have also benefitted from incorporating UAS into their operations. Drones provide livestock producers an eye in the sky to make the naturally challenging task of monitoring herds over large areas more manageable. A few other ways UAS have been utilized in livestock production include detecting diseased animals, measuring the temperatures of animals and feedlot surfaces, determining breeding activities, identifying animals with extreme dispositions, and monitoring grazing activities and pasture health (Bedord, 2015). Similar to crop applications, having access to current data allows livestock producers to make more informed decisions surrounding their operation leading to improved efficiency and overall business performance.

Literature Review on UAS Applications in the Seed Industry

The possibilities for the use of UAS in the seed industry are seemingly endless and are continuously expanding as technologies and sensors improve. There are many UAS field data collection applications currently being explored by the seed industry and depending on the research objectives, may prove to be a useful tool in the data collection and analysis process. Such tools have the possibility to give researchers a new and more informative view of their experiments, while improving the overall efficiency and quality of research activities. A few of the more promising applications for UAS in the seed industry include utilizing UAS technology to aid in the collection and analysis of stand counts, plant spacing, phenotypic traits, and vigor data. In general, these data have historically been difficult to collect using traditional methods, such as hand counting plants and manual phenotype measurements. Due to the inefficiencies associated with traditional methods, UAS can provide an opportunity to vastly improve many seed industry research operations.

Stand Counts and Spatial Analysis

Utilizing UAS for the accurate and efficient collection of stand counts have shown great potential in recent years. Varela et al. (2018) showed that early-season stand counts in corn can be collected via UAS with an overall accuracy percentage of 0.96 compared to ground-truths. The best accuracy was achieved at 2.4 mm resolution corresponding to a flight altitude of 10 m. Higher flight altitudes resulted in decreased accuracy due to degraded resolution. The best results were also achieved when corn plants had between two and three leaves and before leaf-overlapping between plants occurred. Gnädinger and Schmidhalter (2017) had similar accuracy results in their studies. In their experiments, flights were conducted at 50 m on slightly larger corn plants with three to five leaves. An overall correlation of determination (R^2) of 0.89 was achieved with an average error between visually and digitally counted plants of less than 5%. They determined that the best time to assess plant number occurs when young, light-green leaves differ from older, dark-green leaves, and before leaf overlapping between plants occurs. The presence of weeds and blurry effects on the images represented possible errors in counting plants.

Other UAS collected traits that may complement stand count data include the measurement of plant distance within and between rows and the determination of plant skips. Zhang et al. (2018) developed a procedure to calculate maize interval distance using UAS. Accurate results with relative errors of approximately 10% were achieved with flight heights of one to five meters. It has also been shown by Souza et al. (2017) that it is possible to map and calculate skips using images obtained by UAS. In their study, they were able to develop a procedure for analyzing UAS obtained images of sugarcane fields in order to create a map of the skips within the field and also to determine overall skip lengths. An overall coefficient of determination of 0.97 was achieved indicating an excellent relationship between estimated and observed skip lengths.

Phenotyping and Vigor

The use of UAS have the potential to increase the efficiency and objectiveness of the data collection and analysis processes related to phenotypic and vigor traits. Researchers have shown the ability to effectively use UAS to collect and analyze various phenotypic and vigor trait data such as plant heights, crop health, yield, and overall growth and development. Shafian et al. (2018) successfully used UAS to quantify growth parameters in sorghum. A few traits that they were able to quantify included leaf area index, fractional vegetation cover, and yield. Using the normalized difference vegetation index (NDVI), R^2 values of 0.91, 0.89, and 0.58 were achieved respectively when compared to ground-truths. The best flight correlation for yield occurred 74 days after planting during the flowering stage. A previous study conducted by some of the same authors showed similar applications in wheat. Shi et al. (2016) were able to estimate leaf area index and percent canopy cover using NDVI obtained from UAS. Strong correlations of 0.95 and 0.93 were achieved respectively between UAS and ground-truth measurements showing that UAS can be used to accurately estimate certain biophysical properties in wheat. Using a similar NDVI process, Zhang et al. (2018) were able identify and quantify sheath blight in rice. Comparisons between ground measured NDVIs and NDVIs calculated from UAS captured multispectral images were made with strong correlations being determined (R^2 = 0.91, RMSE = 0.85). Using the UAS derived NDVI, the researchers were able to quantify varying levels of sheath blight in field plots with an overall accuracy of 63% compared with ground-based observations.

Plant height is an important phenotypic trait in many crop species as it may be associated with various agronomic attributes such as yield and lodging susceptibility. Monitoring plant heights during a growing season enables researchers to determine growth rates and to assess responses to various biotic and abiotic stresses. Holman et al. (2016) showed that it is possible to use UAS in order to collect plant heights in wheat with accuracies similar to that of manual, rule based methods. In their work, models derived from UAS Structure from Motion (SfM) and Terrestrial Laser Scanner (TLS/LiDAR) were evaluated for their abilities to accurately and efficiently determine plant heights. Both produced Root Mean Squared Errors (RMSE) of 0.03 m compared to hand measurements with the SfM derived model having a slightly better correlation of determination of 0.99 compared to 0.97 for the TLS/LiDAR derived model. Due to higher costs and poor time efficiency of the TLS/LiDAR derived models as a result of a higher number of individual scans required, the SfM method showed to be the better alternative for efficient and high-throughput measurements of plant heights for research applications. Malambo et al. (2018) conducted a more recent study on using UAS SfM for measuring plant heights in corn and sorghum. Measurements were conducted at several different time intervals representing changes in plant height and development. Although performance was not as great as the previously mentioned wheat study, strong correlations between UAS SfM measurements and ground-truths were observed (R^2 = 0.42-0.91, RMSE = 0.11-0.19 m for corn and R^2 = 0.61-0.85, RMSE = 0.12-0.24 m for sorghum). Hu et al. (2018) evaluated several different UAS derived methods for measuring plant heights in sorghum. In their experiments, they compared two existing remote methods, point cloud and reference ground, with a new method termed self-calibration. The self-calibration method required some manual calibration measurements which added to the labor requirements, but proved to significantly increase performance compared to the other two methods. An overall correlation of determination of 0.63 with a RMSE of 0.07 m was achieved with the self-calibration method when calibration measurements were taken on 10% of the plots. Height measurement repeatability of 0.74 was also achieved with the self-calibration method compared with 0.78 for manual measurements indicating acceptable reproducibility.

Purpose of Study

Currently, all field data for early-season stress tolerance characterization of hybrid corn products are collected by individuals manually hand-counting and/or scoring plots then entering the data into a portable electronic data collection device. This requires the coordination of many people and often takes several hours to complete data collection for a single trait. Manually hand-counting plots for early stand counts are prone to human error from both the act of counting the plants and from recording the data into the data collection device. Early plant vigor data collection is prone to subjectivity and ambiguity resulting in potential scoring biases. Although early vigor scoring is defined by certain criteria, it is still inherently subjective as a vigor score is assigned to each plot based on the discretion of the researcher. Literature and experience have shown that modern UAS have the capabilities to calculate stand counts and to assess plant vigor, but it is unknown if such technologies are accurate and efficient enough to be utilized for early-season stress tolerance characterization field data collection. This paper will examine the feasibility of current UAS technologies for the use of collecting early stand counts and assessing early plant vigor to aid in the early-season stress tolerance characterization of hybrid corn products. The information, methods, and results contained within this paper will also contribute to the existing literature on agricultural research use of UAS technology.

MATERIALS AND METHODS

In order to assess the feasibility of utilizing UAS obtained data for early-season stress tolerance characterization, this study had several objectives: 1) to determine if stand count and vigor data could be collected via UAS, 2) when was the optimal time to collect UAS trait data, 3) how the data compared to ground-truths, 4) if the data could be used for early-season stress tolerance characterization, and 5) what improvements could be made to increase accuracy and improve functionality. To carry out this study, several coordinated actions by multiple groups had to be conducted and executed correctly. This included site selection, experiment design, seed filling, planting, flight planning, drone flying, raw drone data processing and analysis, and ground-truth stand counts and vigor scores.

Trial Site

This study was conducted on the designated early-season stress tolerance characterization research field located on the Pioneer Research Farm in Johnston, IA. The trial site was a 3-acre rectangular-shaped field with a corn following soybean rotation (Figure 1). Conventional tillage with a standardized nutrient, weed, and pest management program was implemented on the trial site. The early-season stress tolerance characterization trial was a randomized complete block design containing 1095 hybrid corn entries replicated three times for a total of 3285 individual plots. The entries were made up of commercial and pre-commercial hybrid corn products representing a wide range of relative maturities. Each plot was 13’ in length with 2.5’ row and alley spacing between the plots. The plots were planted on April 11, 2017 using an 8-row ALMACO precision research planter. 30 seeds per 13’ plot were dropped translating to a population of approximately 50,000 plants/acre with an approximate spacing of 4.3” between plants.

Unmanned Aircraft System

The AscTec Falcon 8 octocopter equipped with a Sony A6000 camera was the UAS platform used for the aerial image and data collection process of this study (Figure 2). Flights were conducted by certified drone pilots using preprogrammed, GPS-controlled flight plans. In total, there were 12 image and data collection flights starting at VE and continuing through the V5 growth stage. Flights were conducted on 4/23 (VE), 4/25 (VE), 4/27 (VE), 5/2 (VE), 5/4 (VE), 5/6 (V1), 5/8 (V1), 5/10 (V2), 5/12 (V2), 5/15 (V3), 5/22 (V4), and 6/1 (V5) of 2017. Flight images and data were processed by an analyst team using proprietary methods and software. After processing and analysis, results were displayed in a Microsoft Excel spreadsheet which included flight date, plot number, plot stand, and plot cover. Plot stand was the number of plants the software was able to detect and count per plot from the UAS obtained images using a predictive counting model. Plot cover was the general percent green canopy cover of each plot calculated by the software from the UAS obtained images. The plot cover percentage was calculated by dividing the number of detected green pixels by the total number of pixels per plot image.

Ground-Truth Data Collection

Early Stand Counts

Manual stand counts were taken on May 16, 2017 when the average plant growth stage was V3. Data were collected by a crew of 3-4 counters and 1 data recorder. Counters walked parallel to their assigned row and counted the number of plants in each of the plots. Counters were instructed to count all emerged plants regardless of health or viability. The counts were called out in a cadence by the counters, and the data were entered into an electronic data collection device. The crew worked through the field in a serpentine-like pattern until stand counts were completed on all of the plots.

Early Vigor

Early vigor scores were conducted on May 18, 2017 when the plants were a late V3 average growth stage. Vigor scores were assigned to each plot using a scale of 1-9 with 1 being the least vigorous and 9 being the most vigorous relative to the other plots in the field. The field was first surveyed and high and low vigor plots were identified in order to form a basis for assigning scores. Less vigorous plots were shorter with smaller, thinner leaves while more vigorous plots were taller and more robust with larger leaves. Vigor scores were assigned to each plot by the author and the scores were recorded into an electronic data collection device.

UAS Early Stand Count Feasibility Analysis

In order to determine if UAS could be utilized for early-season stress tolerance characterization stand count data collection, a systematic approach was used to evaluate individual flight data against observed ground-truth data. Similar to previously mentioned literature, accuracy between UAS and ground-truth collected data were determined using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and by a regression analysis from which the correlation coefficient (R) and coefficient of determination (R^2) were calculated. In addition to those evaluation criteria, the overall average stand count for each flight was determined and compared to the average ground-truth stand count collected on May 16, 2017. The total number of counts greater than zero that the UAS was able to collect during an individual flight compared to the total number of plots at the location was also used as a metric to evaluate flight date quality. Stand count analyses were conducted on only non-suppressed plots. Of the total 3285 plots at the trail site, 3130 non-suppressed plots were included in the analysis. Weather data were collected by an on-farm weather station from which accumulated growing degree units (GDU) and GDU based plant growth stage (V-Stage) were determined. RMSE, MAE, average stand count, and the number of counts were calculated using Microsoft Excel. A regression analysis was conducted using TIBCO Spotfire. By utilizing the scatter plot functionality of Spotfire, the R and R^2 values were determined for UAS vs. ground-truth collected stand counts (Figure 3). Each of the 12 flights were analyzed using the above-mentioned criteria, and an overall GDU and V-Stage based optimal timeframe for collecting UAS stand counts was determined for the current early-season stress tolerance characterization field trial experiment design.

UAS Early Stand Count Improvements

Lower Plant Population Densities

As a way to improve upon the accuracy of utilizing UAS for early season stress tolerance characterization early stand count data collection, a few potential changes to the experiment design and analysis process were evaluated. With the trial site having a plant population density equivalent to approximately 50,000 plants/acre within each plot, the plant leaves begin to overlap at an earlier V-Stage compared with that of a lower plant population density. By reducing the plant population density by way of decreasing the number of seeds per plot or increasing the overall plot length, the plants will reach a larger size before leaf-overlapping occurs enabling the software to better detect and count individual plants within a plot (Varela et al., 2018; Gnädinger and Schmidhalter, 2017).

Reduced Plant Population Density Plots

477 plots at the trial site had a planting error where a reduced number of seeds were dropped per plot. Instead of the planned 30 seeds/plot, only an average of 22 seeds/plot were actually dropped translating to a population of approximately 36,500 plants/acre with 6 inches between individual plants. The same regression analysis (Figure 4) and error analysis by flight date was conducted on these reduced population density plots, and the best overall GDU and V-Stage based flight date was determined. These accuracy results were then compared to the results of the original higher population density results.

Error vs. Plot Plant Population Density

In order to quantify the effect of plant population density on accuracy, the RMSEs and MAEs were calculated for each of the ground-truth stand count values vs. the UAS determined counts for the May 8th, 2017 flight. Ground-truth stand counts ranged from 19 to 32 plants/plot corresponding to plant population densities of approximately 31,500 to 53,100 plants/acre respectively. The RMSE and MAE between ground-truth counts and UAS determined counts for each ground-truth stand count value from 19 to 32 plants/plot were calculated using the same Microsoft Excel based method.

2018 UAS Stand Count Algorithm

Improvements to the algorithm that the software used to detect and count individual plants within a plot from UAS obtained images were made for the 2018 North America growing season. Plot images obtained from five of the best 2017 flight dates (5/6, 5/8, 5/10, 5/12, 5/15) as determined by the previously mentioned quality analysis were analyzed by the analyst team using the 2018 algorithm. Similar to the 2017 algorithm, results were displayed in an Excel spreadsheet and included flight date, plot number, and the remote-sensed stand counts for each individual plot. The same quality analysis by flight date which evaluated regression (Figure 5) and the error of UAS vs. ground-truth counts was conducted on the same non-suppressed plots in order to determine the best GDU and V-Stage based flight date. The 477 plots that were planted at a lower population as described above were analyzed using the same regression (Figure 6) and error analyses. The same error analysis for each of the ground-truth stand count values was also conducted to evaluate the effect of plant population density on accuracy. All of the 2018 algorithm results were then compared to the 2017 algorithm results in order to quantify improvements in regards to regression and error of UAS vs. ground-truth stand counts

UAS Early Vigor Feasibility Analysis

As defined by Biology Online, plant vigor is a measure of the increase in plant growth or foliage volume through time after planting (Vigor, 2005). As opposed to traditional manual plot vigor scoring, the UAS obtained plot cover trait provides a quantifiable measure of the plant vigor within each plot at a given time. In order to determine the feasibility of utilizing UAS for assessing early vigor in early season stress tolerance characterization field trials, a systematic approach similar to that of the early stand count feasibility analysis was used. A regression analysis comparing UAS plot cover to ground-truth vigor scores by flight date was conducted using Spotfire on all non-suppressed plots. R and R^2 values were calculated as well as the total number of UAS determined plot cover values for each flight, and a best flight date compared to ground-observed vigor scores was determined.

UAS Plot Cover Normalization

When using the 1-9 vigor scoring method, scores that are assigned to the plots in any given research field should generally be normally distributed i.e. resemble a bell curve. The 1-9 vigor scale typically becomes a 3-7 scale in the field as differentiating plots into nine vigor score categories becomes difficult. A majority of the plots should receive a score of a 5 (average vigor) with some plots receiving a 4 (below average vigor) and a 6 (above average vigor), while only a few plots should receive a 3 (low vigor) and a 7 (high vigor). Using this as a basis, the plot cover values for the 5/15 flight were normalized using Microsoft Excel functionality. Plots that had plot cover values that fell below -2 standard deviations of the mean received a vigor score of a 3; between -2 and -1 standard deviations, a vigor score of a 4; between -1 and 1 standard deviations, a vigor score of a 5; between 1 and 2 standard deviations, a vigor score of 6; and greater than 2 standard deviations, a vigor score of a 7 (Figure 10). By converting the plot cover values to vigor scores, it became possible to directly compare UAS determined vigor to ground-truth observed vigor scores. RMSE and MAE were then able to be calculated for UAS vs. ground-truth vigor scores for each flight date using the same Microsoft Excel based method as previously mentioned.

RESULTS

UAS Early Stand Count Feasibility Analysis

Using RMSE, MAE, R, R^2, average UAS plot stand, and total UAS counts greater than zero, it was determined that the best time to collect UAS data for stand counts based on the current experiment design occurred with the 5/8, 5/10, and 5/12 flights between 238 and 296 accumulated GDUs when plants were V1 and V2 growth stages (Table 1). Flights flown before and after this time frame had increased error, lower correlations, and missing counts. The lowest RMSE and MAE values of 5.38 and 4.63 respectively occurred during the 5/12 flight at 296 GDUs when plants were a late V2 growth stage. The best R and R^2 values of 0.55 and 0.30 respectively were achieved with the 5/8 flight at 238 accumulated GDUs when plants were a V1 growth stage. The average UAS determined stand for the field were similar for the three best flight dates, ranging from 22.0-22.5 compared to 27.1 for the average ground-truth stand count of the field. All three flights also had counts that were greater than zero for more than 99% of the total analyzed plots.

UAS Early Stand Count Improvements

Reduced Plant Population Density Plots

The 477 plots with a reduced population density had significantly reduced error values and better regression analysis results for UAS vs. ground-truth stand counts compared to all the plots as a whole. From conducting the flight quality analysis (Table 2), it was determined that the best flight date was 5/10 at 273 accumulated GDUs when plants were a V2 growth stage. RMSE and MAE values of 1.61 and 1.17 respectively were achieved with R and R^2 values of 0.75 and 0.57 respectively. The average UAS determined stand for these plots on the 5/10 flight date was 20.4 compared to 21.5 for the average ground-truth stand count of the plots. The 5/10 flight also had counts that were greater than zero for 100% of the total analyzed plots.

Error vs. Plot Plant Population Density

Error generally increased as the number of plants per plot increased for the 5/8 flight date (Figure 8). The best RMSE and MAE values of 2.01 and 1.49 respectively were achieved at 20 plants per plot corresponding to a population of 33,189 plants per acre with approximate plant spacing of 6.6 inches (Table 5). The highest RMSE and MAE values of 7.93 and 7.55 respectively occurred on the plots with 32 plants per plot, corresponding to a population of 53,102 plants per acre with approximate plant spacing of 4.1 inches.

2018 UAS Stand Count Algorithm

Using the same flight date quality analysis on the data generated by the 2018 algorithm, it was determined that the best flight date occurred on 5/12 which corresponded to 296 accumulated GDUs when plants were a late V2 growth stage (Table 3). The lowest RMSE and MAE values of 3.75 and 3.20 respectively, and the best R and R^2 values of 0.75 and 0.56

respectively were all achieved with the 5/12 flight date. The average UAS determined stand count of 23.9, which was closest to the average ground-truth determined stand count of 27.1, also occurred with the 5/12 flight date. All of the analyzed flight dates had counts that were greater than zero for more than 99% of the total analyzed plots.

When analyzing the 477 plots with reduced plant population densities using the 2018 algorithm (Table 4), the same 5/12 flight was identified as the best flight date for data quality. RMSE and MAE values were reduced to 1.08 and 0.69 respectively while R and R^2 values increased to 0.84 and 0.71 respectively. The closest average UAS determined stand count of 20.9 compared to the average ground-truth stand count of 21.5 were achieved for the 5/12 and 5/15 flight dates, and all flight dates had counts greater than zero for 100% of the total analyzed plots.

Similar to the analysis of the 5/8 flight using the 2017 algorithm, error generally increased as plot plant population density increased for the 5/12 flight using the 2018 algorithm (Figure 9). The best RMSE and MAE values of 0.92 and 0.52 respectively were achieved at 20 plants per plot corresponding to a population of 33,189 plants per acre with approximate plant spacing of 6.6 inches (Table 6). The highest RMSE and MAE values of 6.06 and 5.64 respectively occurred on plots with 32 plants per plot, corresponding to a population of 53,203 plants per acre with approximate plant spacing of 4.1 inches.

2017 vs. 2018 UAS Stand Count Algorithms

The 2018 UAS stand count algorithm showed improvements compared to the 2017 stand count algorithm in all of the quality metrics evaluated. When comparing the 2017 vs. 2018 stand count algorithm data on a whole field basis, the best RMSE decreased from 5.38 to 3.75, MAE decreased from 4.63 to 3.20, R increased from 0.55 to 0.75, and R^2 increased from 0.30 to 0.56

(Table 7). On the 477 reduced plant population density plots, the best RMSE decreased from 1.61 to 1.08, MAE decreased from 1.03 to 0.69, R increased from 0.75 to 0.84, and R^2 increased from 0.57 to 0.71 (Table 8). Both the 2017 and 2018 UAS stand count algorithms had the lowest error values on plots that contained 20 plants, but the 2018 algorithm performed significantly better than the 2017 algorithm with RMSE decreasing from 2.01 to 0.92 and MAE decreasing from 1.49 to 0.52 (Table 9).

UAS Early Vigor Feasibility Analysis

By conducting a regression analysis on UAS calculated plot cover vs. ground-truth vigor scores, it was determined that the best flight date was conducted on 5/15 (Figure 7). R and R^2 values of 0.42 and 0.18 respectively were achieved with the 5/15 flight date, which corresponded to 360 accumulated GDUs and a V3 average plant growth stage. All flights except for the first two had plot cover values for 100% of the plots. After normalizing the UAS calculated plot cover values and converting them to vigor scores, an error analysis was conducted for each flight. The lowest RMSE and MAE values of 0.66 and 0.38 respectively were achieved with the 5/15 flight (Table 10).

DISCUSSION

In order to assess the feasibility of utilizing UAS obtained data for early-season stress tolerance characterization, this study had several objectives: 1) to determine if stand count and vigor data could be collected via UAS, 2) when was the optimal time to collect UAS trait data, 3) how the data compared to ground-truths, 4) if the data could be used for early-season stress tolerance characterization, and 5) what improvements could be made to increase accuracy and improve functionality. The results showed that stand count and vigor data could be collected using an UAS process, and optimal trait data collection times were determined based on accumulated GDUs and plant growth stage.

For stand counts, it was determined that the best time to collect UAS data was primarily at the V2 plant growth stage. Similar to results in previously mentioned studies (Varela et al., 2018; Gnädinger and Schmidhalter, 2017), the best accuracy occurs when UAS data is collected just before leaf overlapping. Based on the current field experiment design where 30 seeds are planted per 13' plot, leaf overlap started at the V3 plant growth stage as indicated by field observations (Figure 11) and by the results. Having such a high plot plant population density limited how large the plants could be before leaf overlap occurred. This created a narrow timeframe for optimal data collection where plants had to be large enough to be detected and counted by the software, but not so large that leaf over lapping occurred resulting in the software not being able to detect and count individual plants in a plot.

It was shown by the analysis of the 477 lower plant density plots that data quality in terms of RMSE, MAE, R, and R^2 improved when plot plant population densities were lower. The plots were first identified by the planter software as low drop plots that deviated from the expected 30 seed drop. The plots included in this analysis had an average ground-truth stand count of 22 plants per plot, but the counts ranged from 16 to 27 plants per plot. It was also unknown how well the plants within the plots were spaced, which could have affected UAS determined stand count quality. If the plants in the plots were evenly spaced, the best determined flight date should have been expected to occur with a later flight date when plants were bigger allowing for easier detection and counting by the algorithm. Nonetheless, the results showed significant improvements compared to the standard higher plant population density plots.

The error vs. plot plant population density analysis showed the effect of plot plant density on UAS derived stand count accuracy. Similar to the lower plot plant density analysis, actual plant spacing within the plots cannot be determined as most of the plots with lower stand counts included in this analysis were a result of individual plants not emerging from the 30 seeds planted per plot. The number of plots per ground-truth stand count value were also not equal, resulting in an unbalanced analysis, but the overall trend that error increases with plot plant population density was obvious.

The 2018 stand count algorithm showed improvements compared to the 2017 algorithm in all of the quality metrics that were evaluated. The 2018 algorithm proved that it could more accurately detect and count individual plants within a plot better than the 2017 algorithm compared to ground-truth stand counts using the exact same 2017 UAS obtained images. A single best-time-to-fly was determined for the 2018 algorithm compared to the 2017 algorithm where three possible flight dates showed similar quality results. Having the best flight date being 5/12, which was the last flight before the V3 growth stage, suggests that the 2018 algorithm encountered the same issues with leaf overlapping reducing count accuracy. Quality improvements were also observed with the lower plant density plots when using the 2018 stand count algorithm as well as with the error vs. plot plant population density analysis.

Although it was shown that UAS determined stand counts could be collected for early-season stress tolerance characterization, the counts are not currently accurate enough under the current experiment design to be used for analysis and decision making purposes. Since stand count data are a critical component of early-season stress tolerance characterization, RMSE and MAE values of more than 3 plants per plot for the best flight date using the 2018 algorithm are simply too great for the counts to be used. As shown by the low plot plant population density and the error vs. plot plant population density analyses, accuracy can be significantly improved by reducing the plant population density of the plots to populations below 35,000 plants per acre. This could be accomplished by either reducing the number of seeds planted in each 13' plot, or by increasing the overall plot length. Both are viable options and could provide opportunities for future research projects. Continuous improvements are also being made to the UAS stand count algorithm as well as to the flight data collection protocols which should help improve the overall accuracy of future UAS stand count data collections. The rapidly changing and improving technologies encompassing UAS determined stand count capabilities provides amble and necessary future research opportunities in order to assess and measure improvements in accuracy and efficiency.

It was determined from the results that the best flight date for UAS early vigor data collection vs. ground-truth vigor scores occurred on 5/15 when plants were an average V3 growth stage. Being that the 5/15 flight date was the flight that was closet to when the ground-truth vigor scores were actually collected, the outcome was not surprising. Actual correlations between UAS plot cover values and observed vigor scores were not great with the best coefficient of correlation of 0.42 occurring with the 5/15 flight date. The low correlations are likely due to comparing continuous data (UAS plot cover) to categorical data with few categories (ground-truth vigor scores) and from ground-truth scoring inconsistencies.

As a way to compare UAS plot cover values to ground-truth vigor scores more directly, the UAS plot cover values for the 5/15 flight were normalized and vigor scores of 3 to 7 were assigned to each plot based on the plot cover value's standard deviation from the mean. This allowed for RMSE and MAE values to be calculated for each flight. The 5/15 flight had the lowest error values, agreeing with the results from the regression analysis that it was the best flight for collecting UAS vigor scores compared to ground-based observations. RMSE and MAE values of 0.66 and 0.38 respectively may initially appear low, but with only five vigor categories, the error values are relatively high.

Even though UAS determined vigor and ground-truth vigor scores were not in perfect agreement, using an UAS for determining plot vigor is probably a better option than the current ground-based method. Assigning plot vigor scores via the ground-based method is much more subjective, more prone to errors, and is unlikely to be reproducible. Plot vigor scores are supposed to be assigned based on the plot's vigor relative to all of the other plots within the field. Meeting that criteria in larger fields using the ground-based method is nearly impossible as accurately assessing a large field as a whole is not possible from the ground. By utilizing a drone's bird's-eye perspective and quantifying canopy cover in each plot, more rapid, reproducible, and objective results can be achieved.

Although it is the usually the goal for early vigor scores to be normally distributed in order to identify the most and least vigorous plots, it is not usually possible using ground-based methods in large fields (Table 11). By assigning vigor scores based on the normalization of the UAS obtained plot cover values like previously mentioned, it is certain that the vigor scores will be almost perfectly normally distributed (Figure 14). Combining the whole-field perspective capabilities of the UAS with the plot cover normalization method ensures more accurate and unbiased vigor scoring results compared to ground-based scoring methods. For example, in Figure 12 both plots were scored a 6 using the ground-based vigor method, but from using the normalized UAS plot cover method, the top plot received a vigor score of a 7 while the bottom plot received a vigor score of a 4, which is likely a more accurate representation of actual plot vigor. Figure 13 shows a similar example where the top plot was scored a 4 while the bottom plot was scored a 6 using the ground-based vigor scoring method, but both plots received a vigor score of a 6 with the normalized UAS plot cover method.

One obvious drawback of the normalized UAS plot cover method is that plant height is not currently included in the assessment of vigor, which is usually a defining vigor characteristic. As described by Holman et al. (2016) and Malambo et al. (2018), the capability to remotely measure plant height already exists and may provide an opportunity for future research to see if UAS vigor trait collection can be enhanced with the addition of plant height data. The inclusion of NDVI measurements as described by Shafian et al. (2018), and Shi et al. (2016) may also be worth exploring as a way to improve UAS vigor trait collection.

Using UAS technology to collect stand counts and to assess plant vigor on early-season stress tolerance characterization plots not only shows potential to improve the accuracy and objectiveness of trait data, but improvements in overall data collection and analysis efficiency may also be realized. Currently, it takes a crew of five people four hours to collect stand count data, and the same amount of time for a two-person team to collect vigor scores per location. In total, it takes approximately 28 man-hours to collect stand count and vigor data using ground-based methods per location. Using a drone, a two-person team can fly a location in approximately one hour (including flight plan programming, flight time, and drone setup/teardown), and about another hour for a single person to process and analyze the flight images. In total, it takes approximately 3 man-hours per location to collect stand count and vigor data using an UAS (assuming that both stand count and plot cover values can be calculated from the same flight images). With a difference of roughly 25 man-hours per location, it is obvious that efficiency can be greatly improved by utilizing UAS for trait data collection and analysis. A more thorough analysis may reveal additional efficiencies and may provide an opportunity for a future research project.

The use of UAS technology as a way to collect stand counts and to assess plant vigor for the early-season stress tolerance characterization of hybrid corn products shows great potential. It has been shown in this paper that UAS stand counts and vigor scores can be collected, but modifications to the experiment design and to the interpretation of the results need to be made in order to improve accuracy before relying entirely on UAS obtained data for analysis and decision making purposes. By making the necessary modifications, and by continuously incorporating technological enhancements into the UAS data collection and analysis process, stand counts, vigor, and possibly many other agronomically important trait data can be collected and analyzed via UAS. Utilizing such technology can provide more accurate, objective, and efficient data on specific traits of interest resulting in overall higher quality products and cost-savings for the company and their customers.

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FIGURES AND TABLES

Figure 1. Early-season stress tolerance characterization research field flown on 6/1/17.

Figure 2. AscTec Falcon 8 (permission granted by Intel Corporation, 2018).

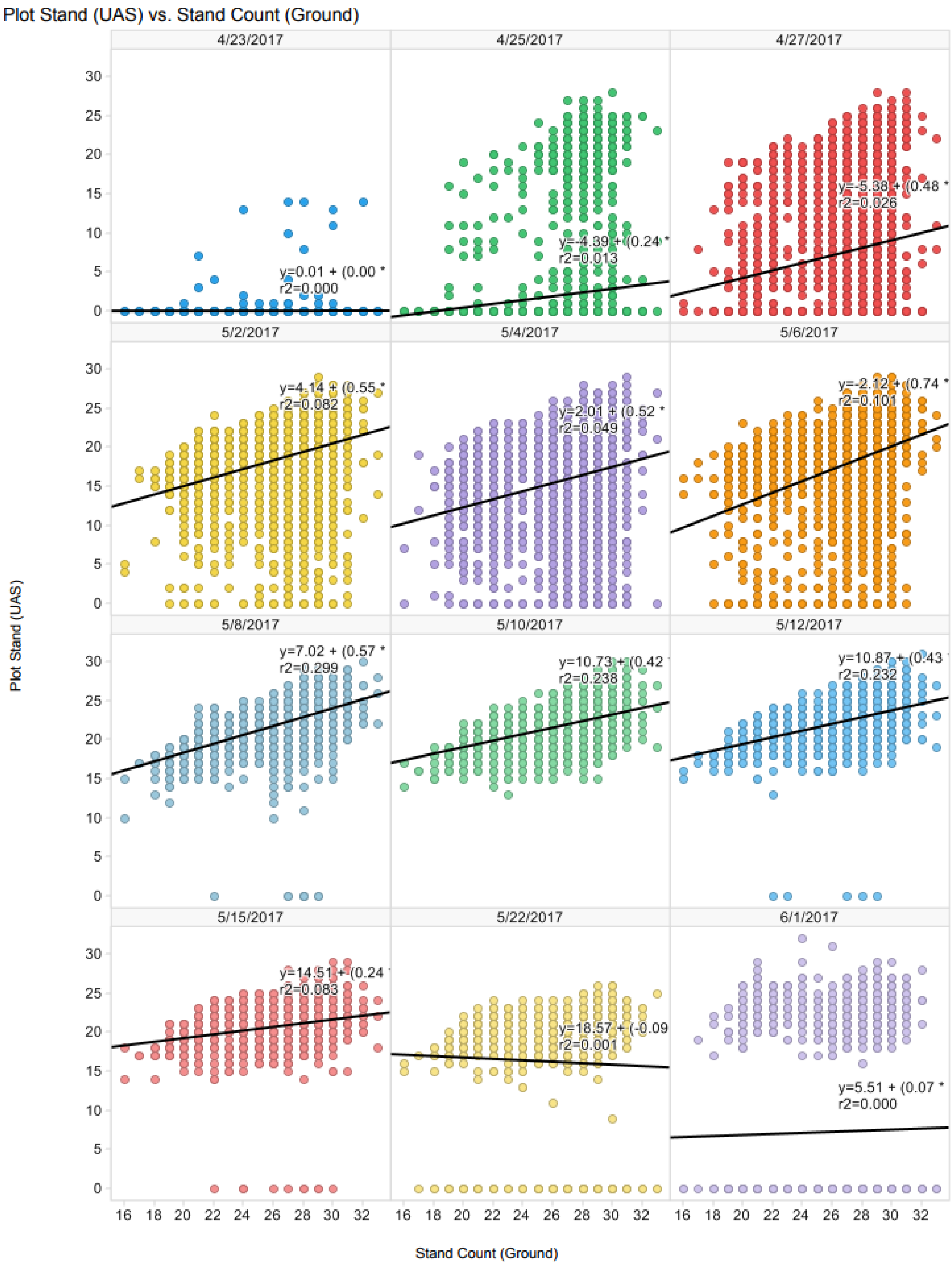

Figure 3. UAS vs. ground-truth stand counts by flight date regression analysis (2017 algorithm).

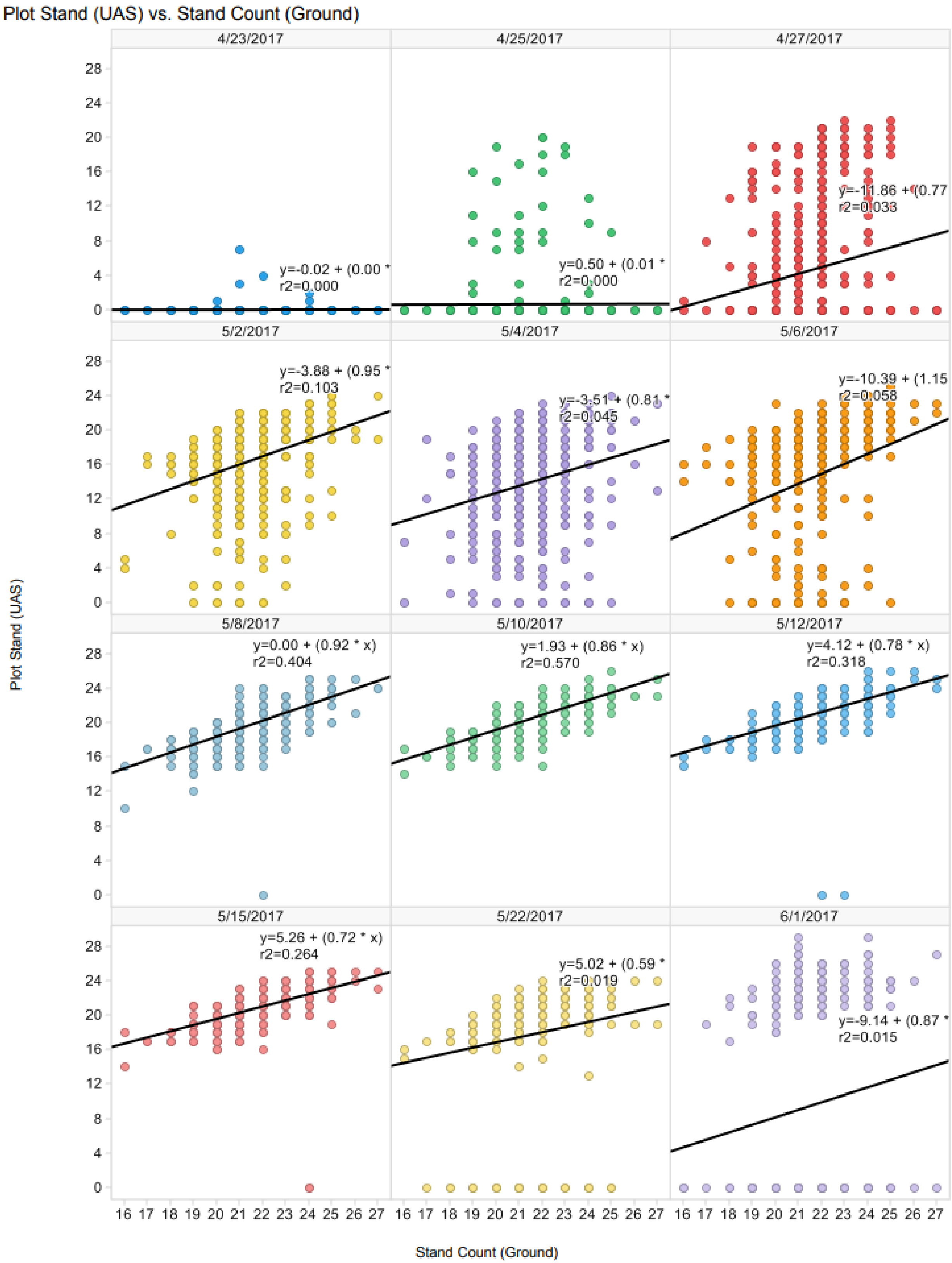

Figure 4. Low drop rate plots - UAS vs. ground-truth stand counts by flight date regression analysis (2017 algorithm).

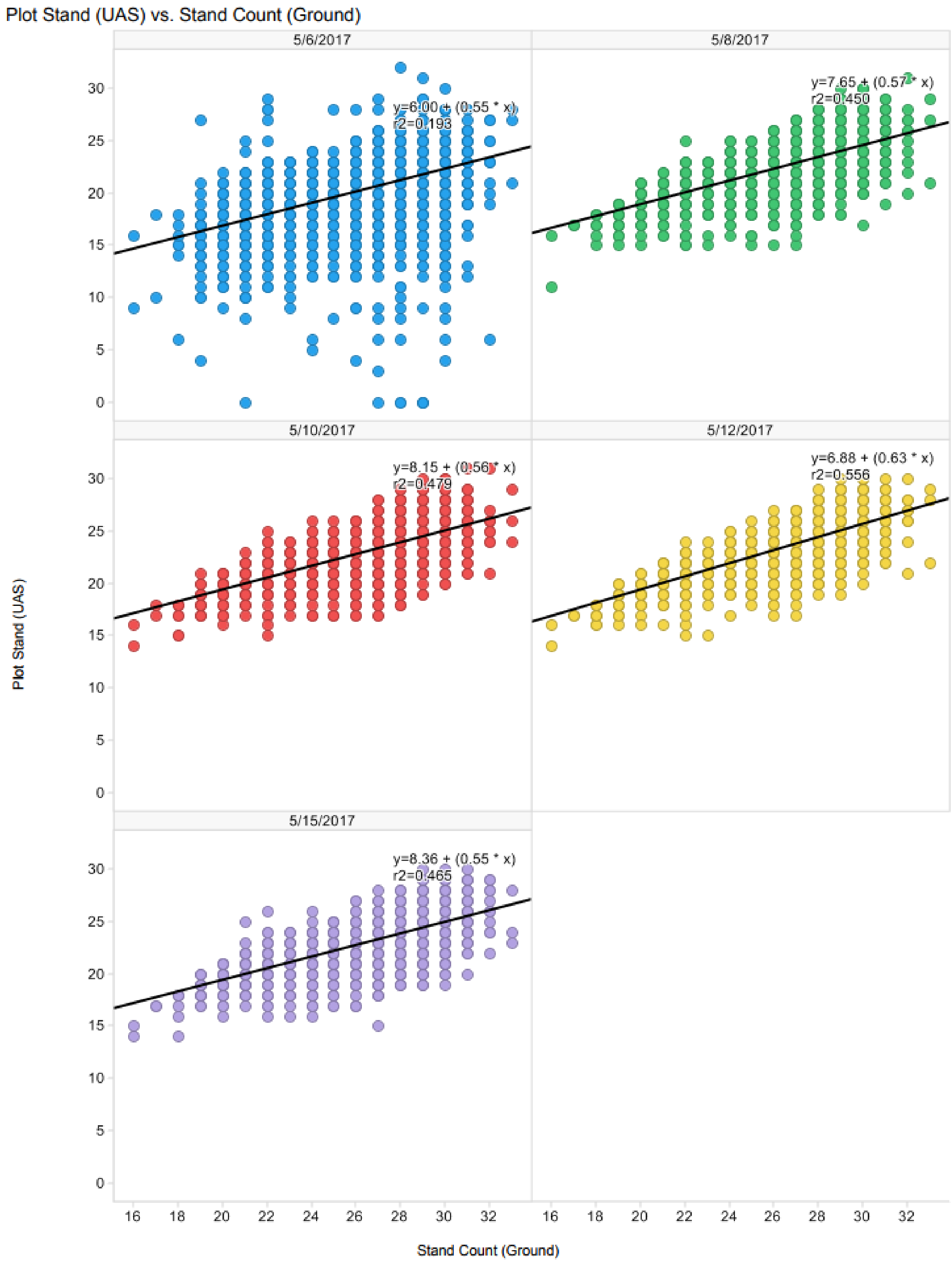

Figure 5. UAS vs. ground-truth stand counts by flight date regression analysis (2018 algorithm).

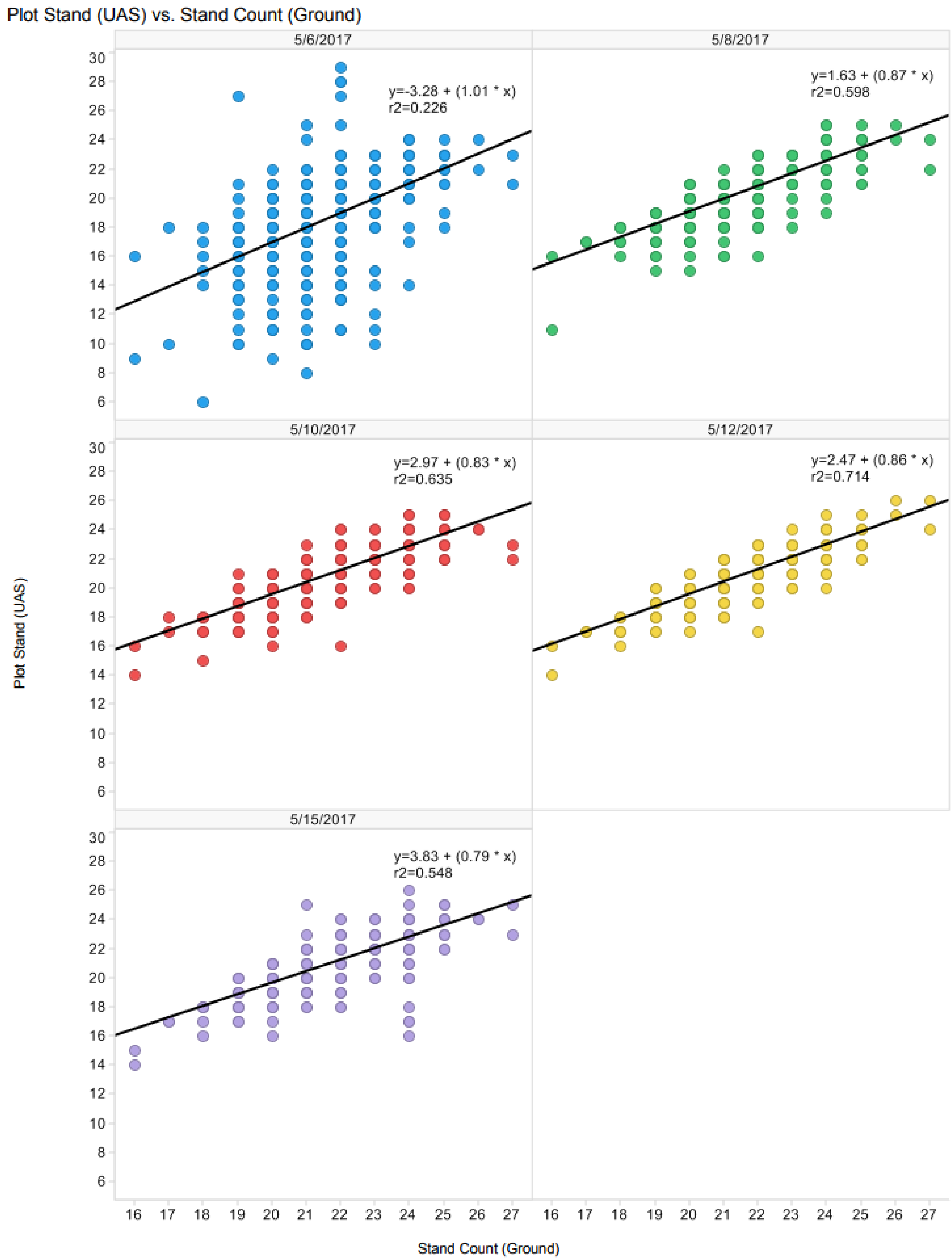

Figure 6. Low drop rate plots - UAS vs. ground-truth stand counts by flight date regression analysis (2018 algorithm).

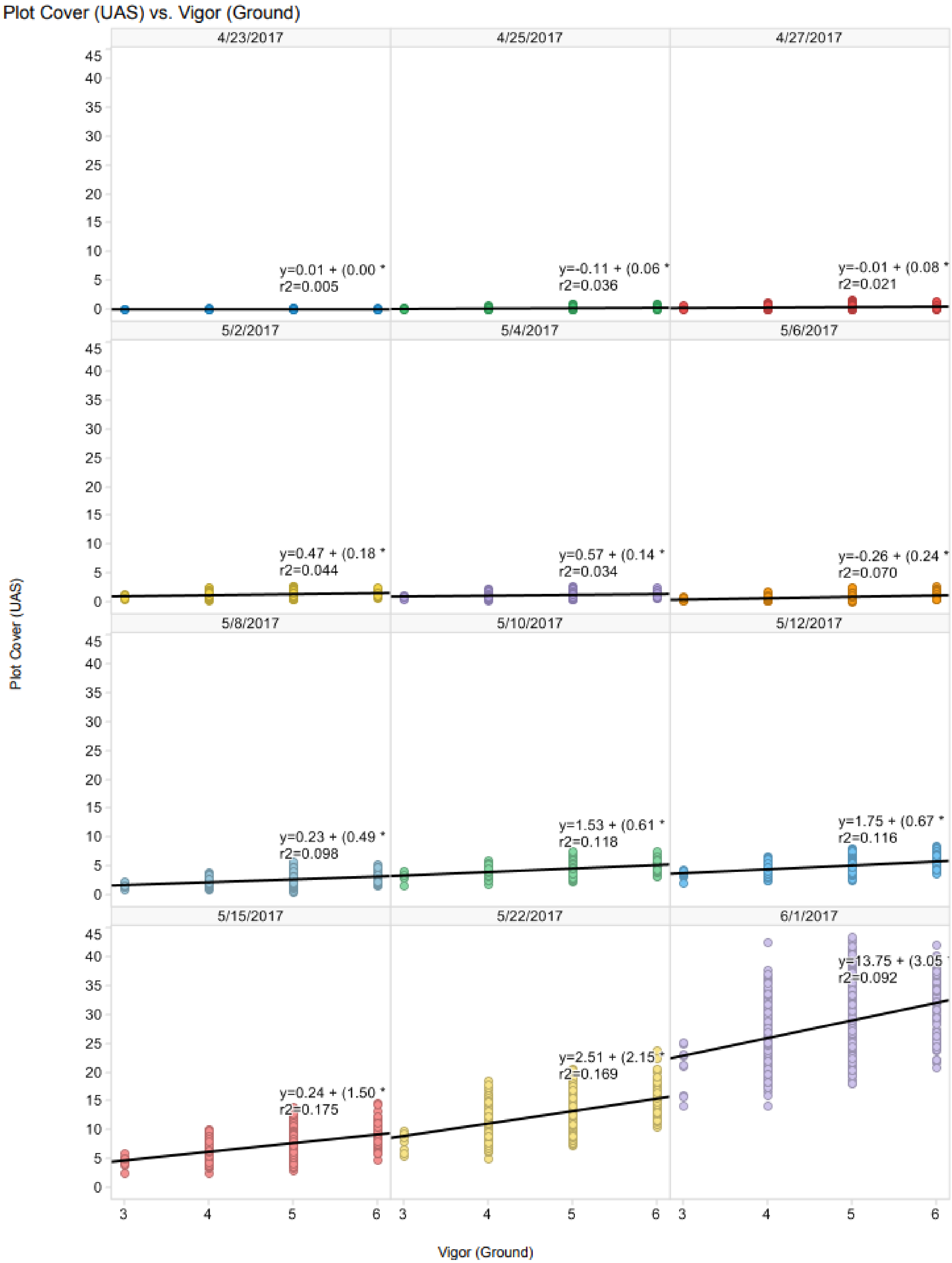

Figure 7. UAS plot cover vs. ground-truth vigor regression analysis.

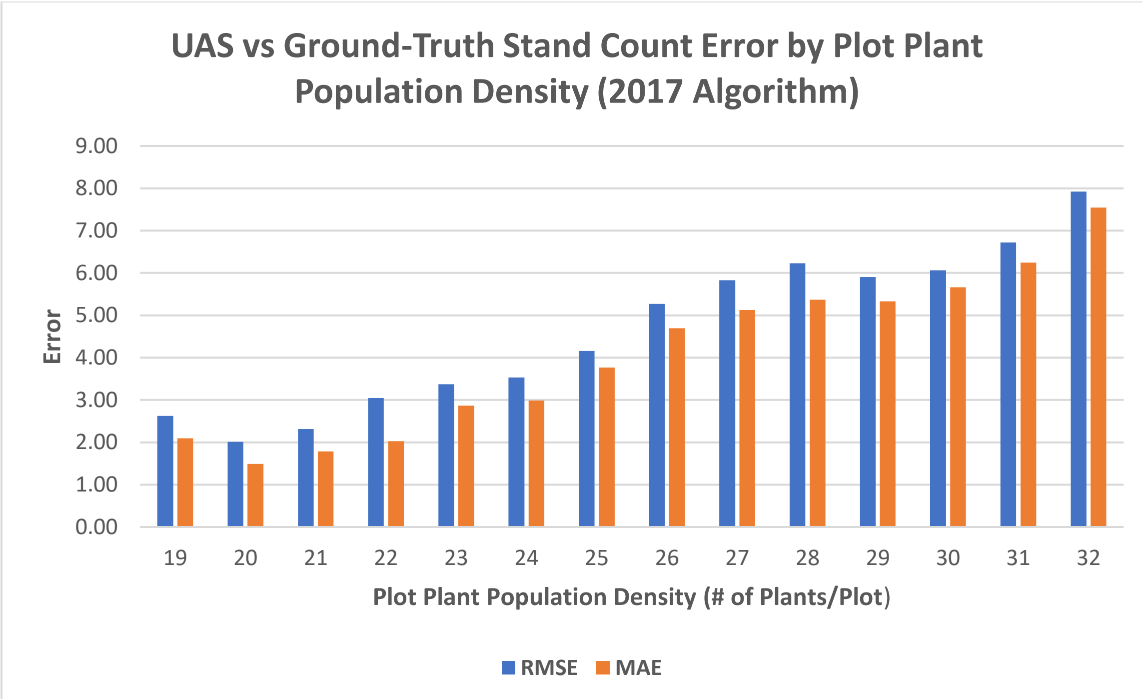

Figure 8. Effect of plot plant density on UAS derived stand count accuracy – 5/8 flight (2017 algorithm).

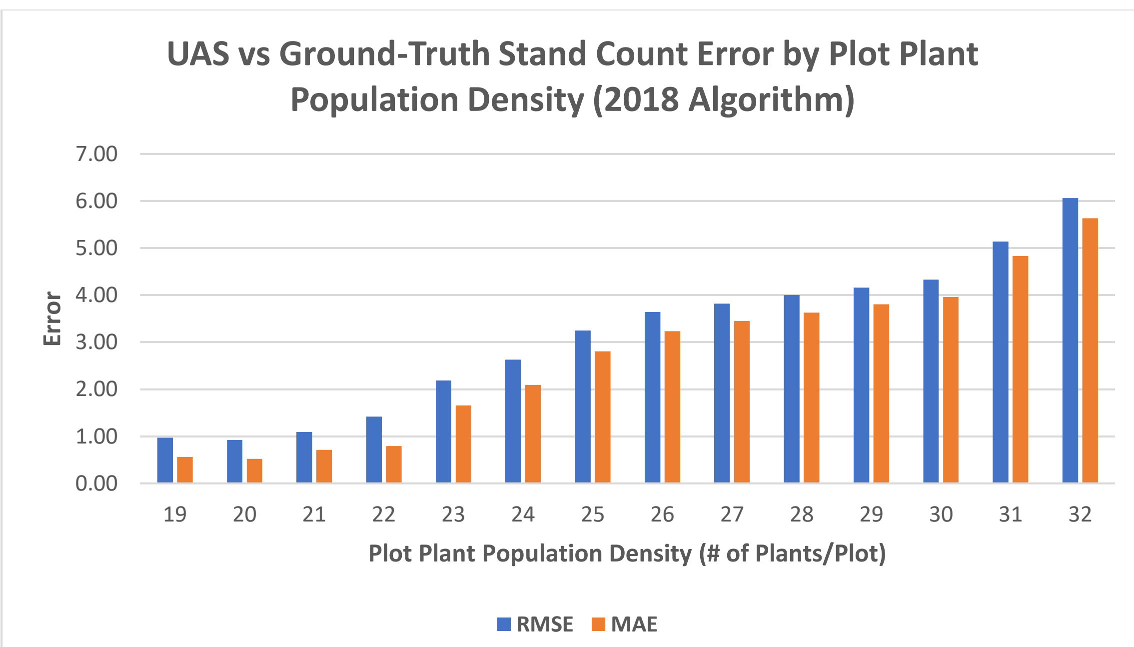

Figure 9. Effect of plot plant density on UAS derived stand count accuracy – 5/12 flight (2018 algorithm).

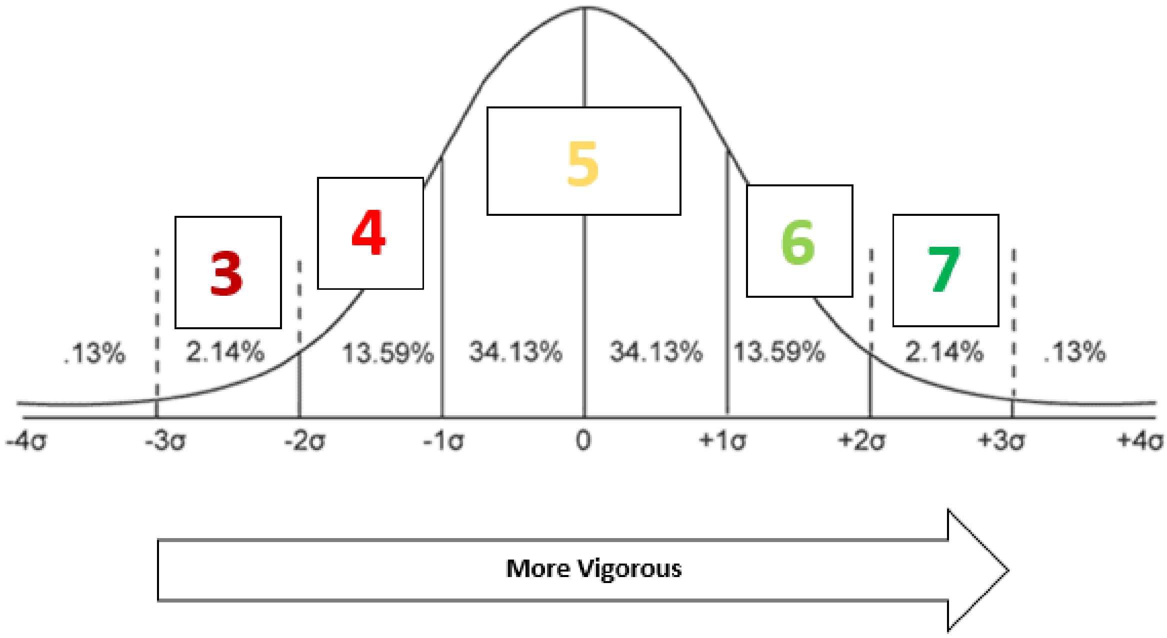

Figure 10. Normalized UAS plot cover vigor scores.

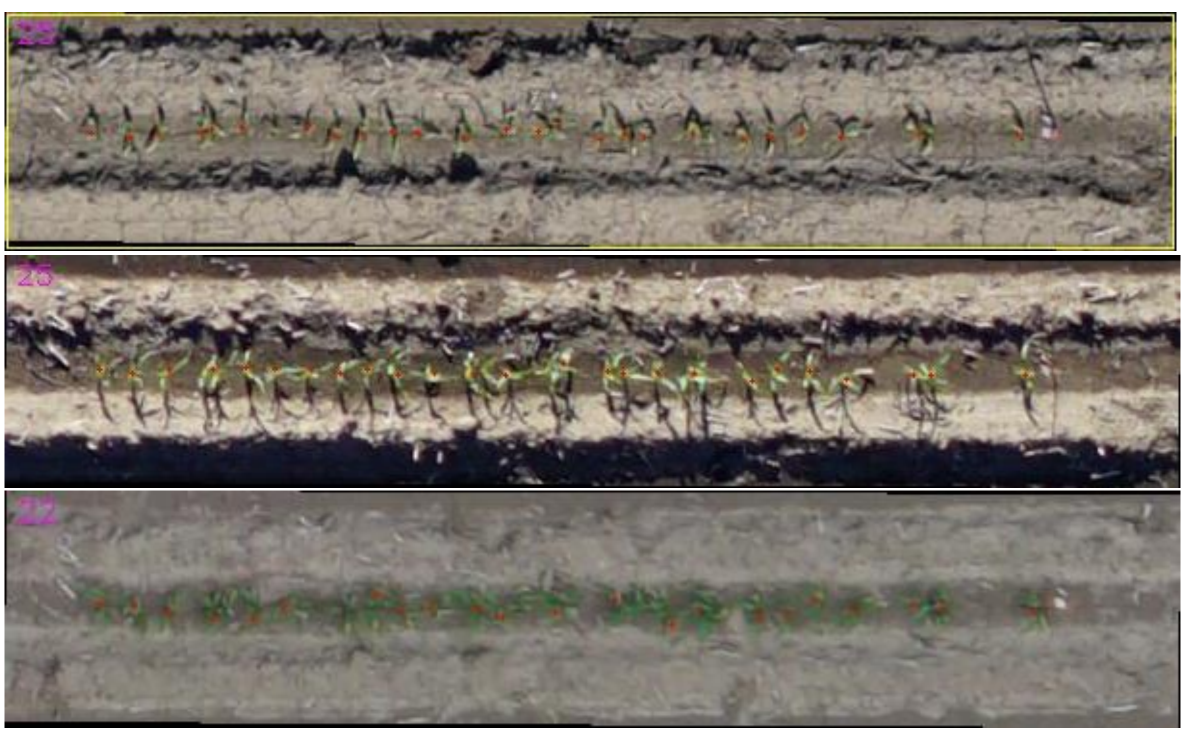

Figure 11. Same plot flown on 5/8 (V1) – top, 5/12 (V2) – middle, and 5/15 (V3) – bottom. Leaf overlap started at V3 – bottom image. UAS determined stand count is indicated in the top left corner of each image. Ground-truth stand count was 25.

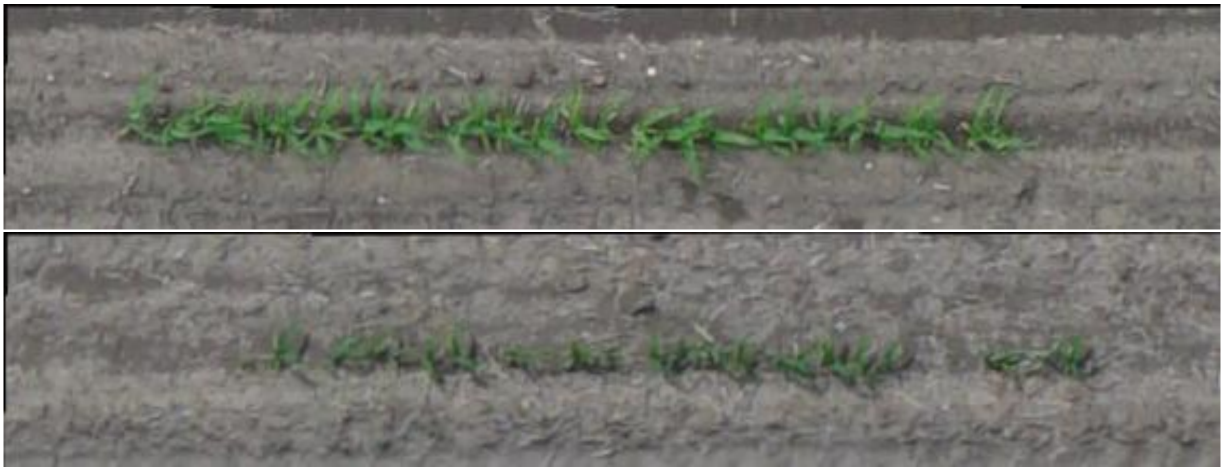

Figure 12. 5/15 flight. Both plots were scored a 6 using the ground-based vigor scoring method. Using the normalized UAS plot cover method, the top plot was scored a 7 while the bottom plot was scored a 4.

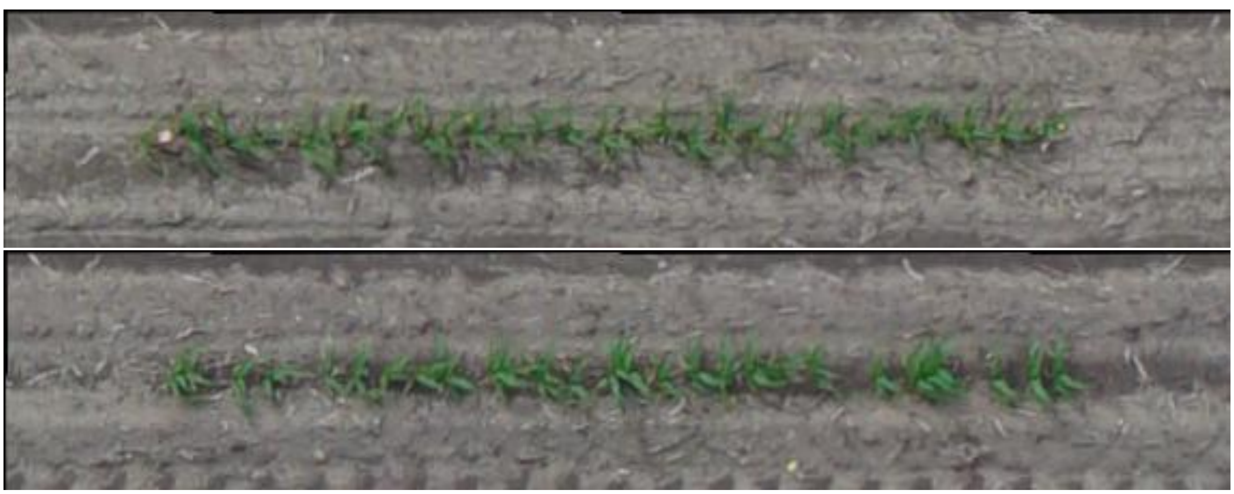

Figure 13. 5/15 flight. Using the ground-based vigor scoring method, the top plot was scored a 4 while the bottom plot was scored a 6. Using the normalized UAS plot cover method, both plots were scored a 6.

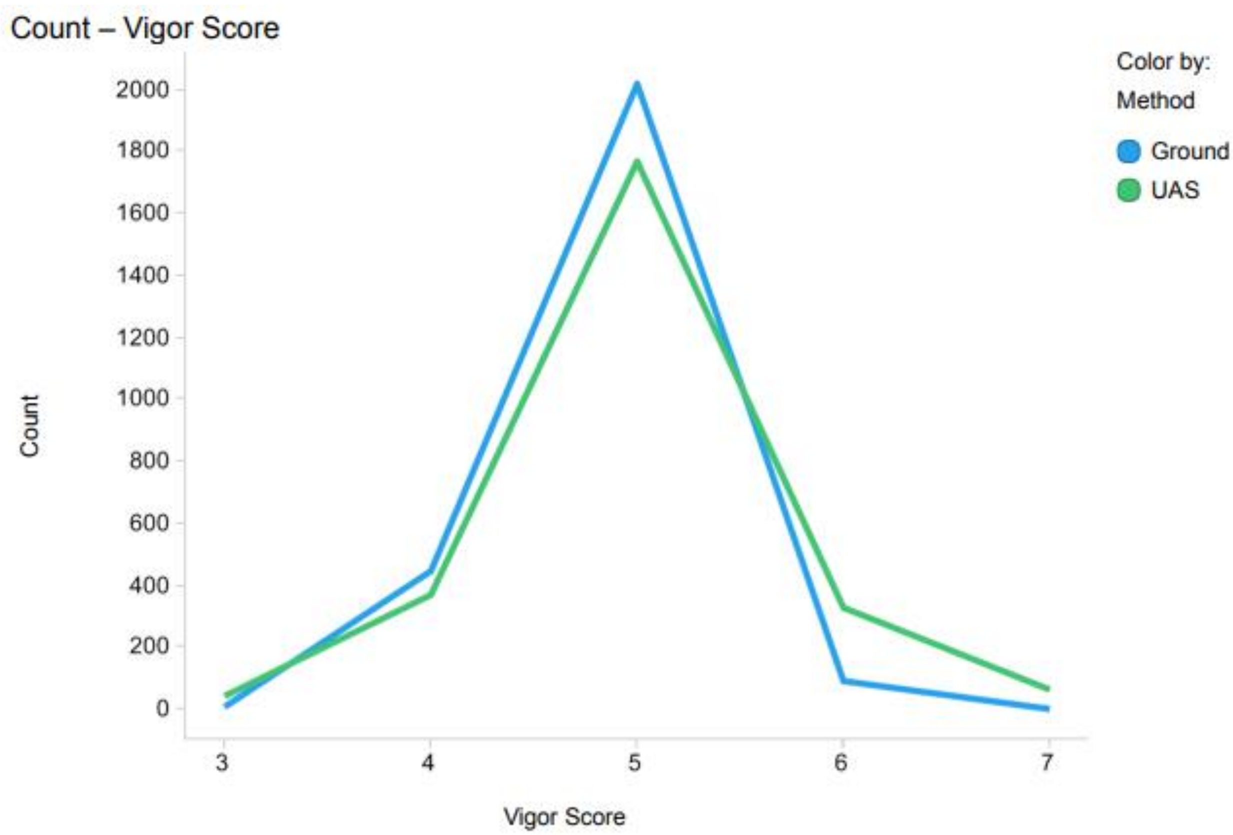

Figure 14. Normal distribution visualization of ground-based vs. UAS vigor assessment methods.

Table 1. Flight analysis (2017 algorithm).

Flight Date	Plant Date	Plants/Ac	Plant Spacing (in)	DAP	Accum GDU	V-Stage	Total Plots	Avg Stand (Ground)	Avg Stand (UAS)	RMSE	MAE	R	R^2	Count (#)	Count (%)
4/23/2017	4/11/2017	50000	4.3	12	134.16	VE	3130	27.1	0.0	27.19	27.02	0.00	0.00	24	0.8
4/25/2017	4/11/2017	50000	4.3	14	157.75	VE	3130	27.1	2.2	25.74	24.90	0.11	0.01	408	13.0
4/27/2017	4/11/2017	50000	4.3	16	160.25	VE	3130	27.1	7.8	21.29	19.43	0.16	0.03	1724	55.1
5/2/2017	4/11/2017	50000	4.3	21	166.73	VE	3130	27.1	19.0	9.85	8.17	0.29	0.08	3057	97.7
5/4/2017	4/11/2017	50000	4.3	23	181.32	VE	3130	27.1	16.1	13.00	11.11	0.22	0.05	2962	94.6
5/6/2017	4/11/2017	50000	4.3	25	205.77	V1	3130	27.1	18.1	11.21	9.12	0.32	0.10	2892	92.4
5/8/2017	4/11/2017	50000	4.3	27	238.26	V1	3130	27.1	22.4	5.50	4.72	0.55	0.30	3120	99.7
5/10/2017	4/11/2017	50000	4.3	29	272.72	V2	3130	27.1	22.0	5.78	5.09	0.49	0.24	3130	100.0
5/12/2017	4/11/2017	50000	4.3	31	296.31	V2	3130	27.1	22.5	5.38	4.63	0.48	0.23	3126	99.9
5/15/2017	4/11/2017	50000	4.3	34	359.75	V3	3130	27.1	21.0	6.92	6.17	0.29	0.08	3120	99.7
5/22/2017	4/11/2017	50000	4.3	41	437.06	V4	3130	27.1	20.1	13.99	10.95	0.03	0.00	2516	80.4
6/1/2017	4/11/2017	50000	4.3	51	560.54	V5	3130	27.1	22.4	22.54	19.94	0.00	0.00	1029	32.9

Table 2. Low drop rate flight analysis (2017 algorithm).

Flight Date	Plant Date	Plants/Ac	Plant Spacing (in)	DAP	Accum GDU	V-Stage	Total Plots	Avg Stand (Ground)	Avg Stand (UAS)	RMSE	MAE	R	R^2	Count (#)	Count (%)
4/23/2017	4/11/2017	36500	6.0	12	134.16	VE	477	21.5	0.0	21.52	21.45	0.00	0.00	6	1.3
4/25/2017	4/11/2017	36500	6.0	14	157.75	VE	477	21.5	0.7	21.09	20.81	0.00	0.00	31	6.5
4/27/2017	4/11/2017	36500	6.0	16	160.25	VE	477	21.5	4.7	18.15	16.90	0.18	0.03	198	41.5
5/2/2017	4/11/2017	36500	6.0	21	166.73	VE	477	21.5	16.6	6.72	5.02	0.32	0.10	467	97.9
5/4/2017	4/11/2017	36500	6.0	23	181.32	VE	477	21.5	14.1	9.65	7.59	0.21	0.05	447	93.7
5/6/2017	4/11/2017	36500	6.0	25	205.77	V1	477	21.5	14.7	10.29	7.18	0.24	0.06	395	82.8
5/8/2017	4/11/2017	36500	6.0	27	238.26	V1	477	21.5	19.8	2.49	1.81	0.64	0.40	476	99.8
5/10/2017	4/11/2017	36500	6.0	29	272.72	V2	477	21.5	20.4	1.61	1.17	0.75	0.57	477	100.0
5/12/2017	4/11/2017	36500	6.0	31	296.31	V2	477	21.5	20.9	1.98	1.03	0.56	0.32	475	99.6
5/15/2017	4/11/2017	36500	6.0	34	359.75	V3	477	21.5	20.7	2.14	1.13	0.51	0.26	475	99.6
5/22/2017	4/11/2017	36500	6.0	41	437.06	V4	477	21.5	20.2	7.72	3.86	0.14	0.02	419	87.8
6/1/2017	4/11/2017	36500	6.0	51	560.54	V5	477	21.5	23.0	16.52	13.40	0.12	0.02	196	41.1

Table 3. Flight analysis (2018 algorithm).

Flight Date	Plant Date	Plants/Ac	Plant Spacing (in)	DAP	Accum GDU	V-Stage	Total Plots	Avg Stand (Ground)	Avg Stand (UAS)	RMSE	MAE	R	R^2	Count (#)	Count (%)
5/6/2017	4/11/2017	50000	4.3	25	205.77	V1	3130	27.1	20.8	7.23	6.36	0.44	0.19	3120	99.7
5/8/2017	4/11/2017	50000	4.3	27	238.26	V1	3130	27.1	23.0	4.68	4.13	0.67	0.45	3130	100.0
5/10/2017	4/11/2017	50000	4.3	29	272.72	V2	3130	27.1	23.4	4.22	3.66	0.69	0.48	3130	100.0
5/12/2017	4/11/2017	50000	4.3	31	296.31	V2	3130	27.1	23.9	3.75	3.20	0.75	0.56	3130	100.0
5/15/2017	4/11/2017	50000	4.3	34	359.75	V3	3130	27.1	23.4	4.29	3.73	0.68	0.47	3130	100.0

Table 4. Low drop rate flight analysis (2018 algorithm).

Flight Date	Plant Date	Plants/Ac	Plant Spacing (in)	DAP	Accum GDU	V-Stage	Total Plots	Avg Stand (Ground)	Avg Stand (UAS)	RMSE	MAE	R	R^2	Count (#)	Count (%)
5/6/2017	4/11/2017	36500	6.0	25	205.77	V1	477	21.5	18.5	4.24	3.24	0.48	0.23	477	100.0
5/8/2017	4/11/2017	36500	6.0	27	238.26	V1	477	21.5	20.4	1.58	1.11	0.77	0.60	477	100.0
5/10/2017	4/11/2017	36500	6.0	29	272.72	V2	477	21.5	20.8	1.24	0.81	0.80	0.64	477	100.0
5/12/2017	4/11/2017	36500	6.0	31	296.31	V2	477	21.5	20.9	1.08	0.69	0.84	0.71	477	100.0
5/15/2017	4/11/2017	36500	6.0	34	359.75	V3	477	21.5	20.9	1.35	0.83	0.74	0.55	477	100.0

Table 5. Error vs. plot plant population density – 5/8 flight (2017 algorithm).

Plants/13' Plot	Plants/Acre	Plant Spacing (in)	# of Plots	RMSE	MAE
19	31529	7.0	32	2.63	2.09
20	33189	6.6	83	2.01	1.49
21	34848	6.3	131	2.32	1.79
22	36508	6.0	148	3.05	2.03
23	38167	5.7	61	3.37	2.87
24	39826	5.5	87	3.53	2.99
25	41486	5.3	124	4.16	3.77
26	43145	5.0	235	5.27	4.69
27	44805	4.8	405	5.83	5.13
28	46464	4.7	613	6.23	5.36
29	48124	4.5	650	5.91	5.33
30	49783	4.3	471	6.07	5.66
31	51442	4.2	65	6.72	6.25
32	53102	4.1	11	7.93	7.55

Table 6. Error vs. plot plant population density – 5/12 flight (2018 algorithm).

Plants/13' Plot	Plants/Acre	Plant Spacing (in)	# of Plots	RMSE	MAE
19	31529	7	32	0.97	0.56
20	33189	6.6	83	0.92	0.52
21	34848	6.3	131	1.09	0.71
22	36508	6	148	1.42	0.79
23	38167	5.7	61	2.18	1.66
24	39826	5.5	87	2.63	2.09
25	41486	5.3	124	3.25	2.81
26	43145	5	235	3.64	3.23
27	44805	4.8	405	3.82	3.45
28	46464	4.7	613	4.00	3.63
29	48124	4.5	650	4.16	3.80
30	49783	4.3	471	4.33	3.96
31	51442	4.2	65	5.14	4.83
32	53102	4.1	11	6.06	5.64

Table 7. 2017 vs. 2018 UAS stand count algorithm quality comparison. Highlighted cells indicate best column value while cells highlighted dark green indicate best categorical value.

	RMSE		MAE		R		R^2	
Flight Date	2017	2018	2017	2018	2017	2018	2017	2018
5/6/2017	11.21	7.23	9.12	6.36	0.32	0.44	0.10	0.19
5/8/2017	5.50	4.68	4.72	4.13	0.55	0.67	0.30	0.45
5/10/2017	5.78	4.22	5.09	3.66	0.49	0.69	0.24	0.48
5/12/2017	5.38	3.75	4.63	3.20	0.48	0.75	0.23	0.56
5/15/2017	6.92	4.29	6.17	3.73	0.29	0.68	0.08	0.47

Table 8. Low drop rate 2017 vs. 2018 UAS stand count algorithm quality comparison. Highlighted cells indicate best column value while cells highlighted dark green indicate best categorical value.

	RMSE		MAE		R		R^2	
Flight Date	2017	2018	2017	2018	2017	2018	2017	2018
5/6/2017	10.29	4.24	7.18	3.24	0.24	0.48	0.06	0.23
5/8/2017	2.49	1.58	1.81	1.11	0.64	0.77	0.40	0.60
5/10/2017	1.61	1.24	1.17	0.81	0.75	0.80	0.57	0.64
5/12/2017	1.98	1.08	1.03	0.69	0.56	0.84	0.32	0.71
5/15/2017	2.14	1.35	1.13	0.83	0.51	0.74	0.26	0.55

Table 9. 2017 vs. 2018 UAS stand count algorithm comparison on error vs. plot plant population density. Highlighted cells indicate best column value while cells highlighted dark green indicate best categorical value.

				RMSE		MAE	
Plants/13' Plot	Plants/Acre	Plant Spacing (in)	# of Plots	2017	2018	2017	2018
19	31529	7	32	2.63	0.97	2.09	0.56
20	33189	6.6	83	2.01	0.92	1.49	0.52
21	34848	6.3	131	2.32	1.09	1.79	0.71
22	36508	6	148	3.05	1.42	2.03	0.79
23	38167	5.7	61	3.37	2.18	2.87	1.66
24	39826	5.5	87	3.53	2.63	2.99	2.09
25	41486	5.3	124	4.16	3.25	3.77	2.81
26	43145	5	235	5.27	3.64	4.69	3.23
27	44805	4.8	405	5.83	3.82	5.13	3.45
28	46464	4.7	613	6.23	4.00	5.36	3.63
29	48124	4.5	650	5.91	4.16	5.33	3.80
30	49783	4.3	471	6.07	4.33	5.66	3.96
31	51442	4.2	65	6.72	5.14	6.25	4.83
32	53102	4.1	11	7.93	6.06	7.55	5.64

Table 10. UAS vs. ground-truth vigor flight analysis.

Flight Date	Plant Date	DAP	Accum GDU	V-Stage	Total Plots	R	R^2	RMSE	MAE	Count (#)	Count (%)
4/23/2017	4/11/2017	12	134.16	VE	2567	0.07	0.01	0.74	0.40	2490	97.0
4/25/2017	4/11/2017	14	157.75	VE	2567	0.19	0.04	0.76	0.46	2566	100.0
4/27/2017	4/11/2017	16	160.25	VE	2567	0.14	0.02	0.78	0.48	2567	100.0
5/2/2017	4/11/2017	21	166.73	VE	2567	0.21	0.04	0.75	0.46	2567	100.0
5/4/2017	4/11/2017	23	181.32	VE	2567	0.18	0.03	0.77	0.46	2567	100.0
5/6/2017	4/11/2017	25	205.77	V1	2567	0.26	0.07	0.73	0.44	2567	100.0
5/8/2017	4/11/2017	27	238.26	V1	2567	0.31	0.10	0.71	0.43	2567	100.0
5/10/2017	4/11/2017	29	272.72	V2	2567	0.34	0.12	0.70	0.42	2567	100.0
5/12/2017	4/11/2017	31	296.31	V2	2567	0.34	0.12	0.70	0.41	2567	100.0
5/15/2017	4/11/2017	34	359.75	V3	2567	0.42	0.18	0.66	0.38	2567	100.0
5/22/2017	4/11/2017	41	437.06	V4	2567	0.41	0.17	0.68	0.39	2567	100.0
6/1/2017	4/11/2017	51	560.54	V5	2567	0.30	0.09	0.71	0.43	2567	100.0

Table 11. Vigor score normal distribution comparison for ground-based vs. UAS methods.

Ground				
Vigor Score	Total Plots	Normal Distribution	Count	Observed Distribution
3	2567	2.2	10	0.4
4	2567	13.6	447	17.4
5	2567	68.2	2019	78.7
6	2567	13.6	91	3.5
7	2567	2.2	0	0.0
UAS				
Vigor Score	Total Plots	Normal Distribution	Count	Observed Distribution
3	2567	2.2	41	1.6
4	2567	13.6	369	14.4
5	2567	68.2	1766	68.8
6	2567	13.6	326	12.7
7	2567	2.2	65	2.5